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Investigating the effect of a robotic tutor on learner perception of skill based feedback

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Abstract. In this paper we investigate the effect of different embodiments on perception of a skill based feedback (a basic open learner model) with a robotic tutor. We describe a study with fifty-one 11-13 year old learners. Each learner carries out a geography based activity on a touch table. A real time model of the learner's skill levels is built based on the learner's interaction with the activity. We explore three conditions where the contents of this learner model is fed back to the learner with different levels of embodiment: (1) Full embodiment, where skill levels are presented and explained solely by a robot; (2) Mixed embodiment, where skill levels are presented on a screen with explanation by a robot; and (3) No embodiment, where skill levels and explanation are presented on a screen with no robot. The findings suggest that embodiment can increase enjoyment, understanding, and trust in explanations of an open learner model.

Keywords: Open Learner Modelling, Learner Modelling, Social Robots.

1 Introduction

Experienced teachers and computer based learning systems allow a scenario where a learner carries out an activity and receives feedback on their areas of strengths and weaknesses contemporaneously. This scenario enables the learner to reflect, correct any errors, and build upon their strengths as they progress through the activity. This type of one-on-one tutoring benefits the student [21]. We aim to emulate such an approach with an interactive activity that can model the skill levels of a learner in real time and provide feedback via a robotic tutor. This will allow us to investigate if a robotic tutor is able to present feedback in a more effective way when compared to on-screen feedback alone. To that end we have investigated the effect of different embodiments on the learner's perception of feedback and overall experience. The learning activity is a geography exercise targeted at 11–13 year old learners. A basic model of the learner's map reading skills is built; "the learner model". We explore three conditions where the contents of this learner model is fed back to the learner with different levels of embodiment: (1) Full embodiment, where skill levels are presented and explained solely by a robot; (2) Mixed embodiment, where skill levels are presented on screen with explanation by a robot; and (3) No embodiment, where skill levels and explanation are presented on a screen with no robot. We ask a series of Likert style questions to investigate enjoyment, perception, and trust of the presentation of the learner model. The findings suggest that embodiment may increase enjoyment, understanding, and trust in explanations of skill levels.

2 Related work

One approach used within intelligent tutoring systems to give skill based feedback is open learner modelling. Open learner models externalise the learner model in a way that is interpretable by the user [3], e.g. skill meters [16]. One of the aims of opening the learner model to the learner is to promote reflection and raise awareness of their understanding or developing skills [4].

A number of systems have used virtual embodiment to teach or interact with the user [9, 5], although results are mixed in terms of learning gain there are many positive effects gained such as enjoyment, motivation [18], and the learners perception of the learning experience [13]. Studies that compared virtual representations of characters with robots showed a preference for robotic embodiment with reference to social presence [10, 12], enjoyment [19, 11, 22], and performance [8]. Greater learning gains have also been shown with a robotic tutor when compared to a virtual tutor [15]. The development of trust can also be increased with the presence of embodiment [7].

Greater learning gains have been shown when personalising robot behaviour to the learner. Recall levels have been higher with a robotic tutor when adaptive cues have been given based on EEG measurements of engagement [20]. Puzzle solving times have been reduced when using personalised tutorials delivered by a robotic tutor [14].

3 Methodology

We aim to apply the benefits of a physically embodied robotic tutor to present an open learner model to the learner. No previous robot tutor research, however, investigates embodiment of on presentation of an open learner model. The robotic tutor may lead to the learner paying more attention due to the feedback being more enjoyable, engaging or the learner affording greater respect to the robot [2]. Understanding which pieces of information are best delivered by a robot and which by on screen elements is useful for the design of systems that include a robot. We aim to investigate and measure how and to what extent the learners accept personal skill based feedback from a physical entity when compared with a computer/touch screen. One of the factors that may be increased with a robotic embodiment is trust. However, there has been little work empirically in this area comparing automated aids vs robotic aids [7].

We use a number of metrics to measure if and to what extent there are advantages brought by a physical embodiment to the presentation and explanation of skill levels. The study endeavours to understand the effect of embodiment on a learner's perception of skill level, trust in the system, enjoyment, and overall experience.

3.1 Scenario

The learners interact with the learning activity individually on a touch screen. The learner is provided with regular updates on the level of their map reading skills and a simple explanation of why the skill level is at its current level.

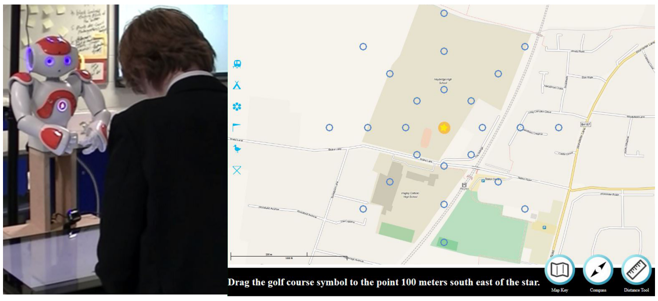

Fig. 1. NAO Robot, Learner, and Learning Task

Learning activity The learners are asked to carry out a geography object placement activity. The activity is designed to test *compass reading*, *map symbol knowledge*, and *distance measuring* competencies. The content conforms to the England and Wales National Curriculum for Geography [1]. Previous mock up studies with both teachers and students identified that the level of difficulty in the activity is appropriate for the learners.

The activity comprises a number of steps that tests all three competencies that are modelled. The questions are in the form of: *"Drag the campsite symbol to the point 100m north of the star"*. After each step in the activity the learner is presented with the current skill levels for each competency and a short explanation of why the skill level is at that level and what has been answered correctly and/or incorrectly. We wanted the system to not only deliver a value for each skill level but also a brief explanation of why the skill level is at that current level as this provides more aspects of feedback to investigate. The explanations are also summarised where possible to reduce repetition if all of the skills have changed in the same way. The learner is provided with three tools to assist them if they are having trouble with the activity. They have the option to open a map key, use a distance tool, and display a compass on screen.

Learner model The construction of the underlying learner model is critical. One of the main approaches to skill modelling is Constraint Based Modelling (CBM) [6, 23, 24]. CBM is a technique that can be used to model a learner's domain knowledge and skill. It does so by checking a learner's answers against a set of relevant constraints; if an answer does not violate a constraint then that answer is correct [17]. Using this approach a basic learner model containing the competencies *compass reading*, *map symbol knowledge*, and *distance measuring* is built. The model provides an indication of the current skill levels calculated using a weighted average so that more up to date information is more relevant than old information. The time taken to answer a question also affects the update of the learner model.

3.2 Procedure

Participants There were fifty-one (twenty-three female, twenty-eight male) participants of mixed ability learners from 3 schools. The learners were aged between 11 and 12 and all in year 7. There was a roughly equal gender balance and ratio of learners from each school across the conditions.

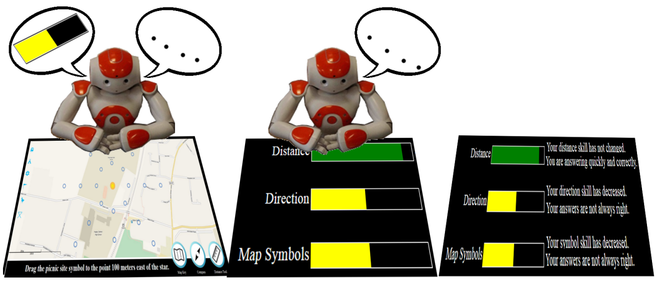

Fig. 2. Conditions, (1) Full embodiment, (2) Mixed embodiment, (3) No embodiment

Experimental Conditions

Full embodiment: Verbal communication of both the skill levels and explanation by the robot There is no visual representation of the skill meter on screen, the skill levels and explanation of the skill level is spoken solely by the robot. The robot makes idle motions throughout.

Mixed embodiment: Skill meter on screen with verbal communication of the explanation of skill level by the robot Each competency is displayed on screen as a skill meter and the robot provides the explanation. There is no on-screen explanation and the robot does not say the skill levels. The robot makes idle motions throughout.

No embodiment: Skill meters and text to present explanation on screen No robot is present in this condition. The skill meters are displayed on screen with a text explanation to the side. If the explanation is the same, the text is summarised in one piece of text. The text is the same as the robotic explanation.

The study was conducted in a meeting room in the learner's school. The activity ran on a touch screen laid flat on the table. The learner was stood up to enable them to comfortably reach all areas of the touch screen. The robot was positioned on a stand opposite the touch table in order for it to be at a similar height to the learner.

The learner was brought in to the room, given a overview of the study and asked to complete a pre-activity questionnaire. The activity and the use of the map tools were explained. The learner then carried out the activity for 4 minutes (time based on experience from a pilot study). The participant was then asked to complete the post-activity questionnaire. During the activity, after each step the learner was presented with the skill level for each competency and an explanation of why the skill level was at that level. This is communicated via a pop-up on screen or via verbal communication from the robot. All three of the conditions provide the same information and explanation, however each condition varies the way the information is presented. There are five skill levels for each competency ranging from very low, low, okay, good, to very good. The learner was informed of their level of skill, followed by how that level has changed since the last step; increased, decreased, or stayed the same. This was then followed by an explanation. There are just three explanations given. If the competency has increased due to a quick answer or stayed the same due to the maximum skill level being reached the explanation is "You are answering quickly and correctly". If the competency increases or stayed the same based on an answer that is correct but not quick the explanation is "You are answering correctly but sometimes a bit slowly". If the competency decreases due to an incorrect answer or has stayed the same due to the lowest skill level the explanation is "Your answers are not always right". If all competencies have updated in the same manner the explanation is summarised rather than explained multiple times. This saves time and avoids repitition.

Data collection The primary form of data collection is a self-report questionnaire containing questions designed to elicit the learner's perceived skill level, enjoyment, engagement, perception, understanding, and trust in the learner model and system. The questionnaire is divided into three sections of Likert style questions: 1) Enjoyment, including "I enjoyed the overall experience" and "I enjoyed the explanation of how and why my skills changed"; 2) Perception/ Understanding, including "I noticed that the system understood my skill levels"; and 3) Trust, including "I trust the explanation of why my skill levels are changing".

4 Experimental results

4.1 Data analysis

Responses to the Likert scale questions were grouped in to Enjoyment, Perception and Trust. The reliability of these groupings was assessed using Cronbach's alpha. The mean values of each group and the individual items were analysed by comparing each condition against each other using a Mann-Whitney U test. The significant values (lower than 0.05) were then further investigated.

4.2 Results

Table 1. Results table

Question	Mean values						Mann-Whitney U Test					
	Mixed		None		Full		Mixed vs None		Full vs None		Full vs Mixed	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	U	p	U	p	U	p
Enjoyment												
Combined	4.52	0.33	4.05	0.66	4.46	0.44	80.0	0.026	89.5	0.057	137.5	0.812
I enjoyed the overall experience	4.82	0.39	4.18	1.01	4.71	0.47	82.0	0.031	97.0	0.106	127.5	0.563
I enjoyed doing the activity	4.76	0.44	4.24	0.75	4.71	0.47	87.5	0.049	94.5	0.085	136.0	0.786
I enjoyed being shown my skill levels throughout the activity	4.59	0.51	4.24	0.97	4.65	0.49	115.5	0.322	107.5	0.205	136.0	0.786
I enjoyed the explanation of how and why my skills changed	4.47	0.51	3.88	0.70	4.59	0.62	79.5	0.024	68.5	0.008	123.5	0.474
I lost track of time while doing the activity	3.75	1.06	3.81	1.22	3.76	1.03	120.0	0.780	128.0	0.790	135.0	0.986
I would like to play the activity again	4.71	0.59	4.00	1.10	4.35	0.70	79.5	0.041	114.0	0.444	102.5	0.150
Perception/Understanding												
Combined	4.65	0.28	4.13	0.63	4.41	0.47	67.0	0.007	107.5	0.205	102.0	0.150
I noticed that the system understood my skill levels	4.71	0.47	3.82	0.95	4.47	0.51	58.0	0.002	84.0	0.038	110.5	0.245
I noticed that the system showed me my skill levels	4.76	0.44	4.18	0.73	4.35	0.61	79.0	0.024	126.5	0.540	91.5	0.067
I noticed that the system explained why my skill levels were changing	4.59	0.51	4.18	0.73	4.53	0.62	100.0	0.131	105.5	0.182	141.0	0.919
I understood when the system showed me my skill levels	4.53	0.51	4.29	1.05	4.29	0.59	136.5	0.786	126.5	0.540	115.0	0.322
I understood the explanation of why my skill levels were changing	4.65	0.61	4.18	0.73	4.41	0.62	91.5	0.067	119.5	0.394	112.5	0.274
Trust												
Combined	4.43	0.42	4.18	0.67	4.22	0.51	112.5	0.274	143.5	0.973	108.0	0.218
I trust that the system can gauge my skill levels correctly	4.29	0.69	4.06	0.97	4.18	0.64	128.5	0.586	143.5	0.973	129.5	0.610
I trust that the skill levels shown by the system were accurate	4.18	0.64	4.29	0.59	4.24	0.56	131.0	0.658	136.5	0.786	138.5	0.838
I trust the explanation of why my skill levels were changing	4.82	0.39	4.25	0.86	4.24	0.75	80.5	0.045	130.5	0.845	80.5	0.026

4.3 Enjoyment

The Cronbach's Alpha for the grouping of enjoyment questions was 0.76. Between the mixed embodiment and no embodiment conditions the overall enjoyment is significantly higher in favour of the mixed condition (U = 80; p= 0.026). At an individual level this was due to these questions having significantly higher values in the mixed condition: "I enjoyed the overall experience" (U = 82; p=0.031423), "I enjoyed doing the activity" (U=87.5, p = 0.048686), "I enjoyed the explanation of how and why my skills changed" (U=79.5; p=0.023766), "I would like to play the activity again" (U=79.5; 0.040674). When comparing the full embodiment and no embodiment conditions, overall, there was no significant difference, however the following question had a significantly higher result: "I enjoyed the explanation of how and why my skills changed" (U=68.5; p =0.007611); There were generally higher values across the other questions but not to a significant level. Between the mixed embodiment and full embodiment there were no significant differences. Across all conditions the following question showed no significant difference: "I enjoyed being shown my skill levels throughout the activity". It appears that embodiment played a limited role in the showing of skill levels but had more significance in the explanation.

4.4 Perception/understanding of the model

The Cronbach's Alpha for the grouping of perception questions was 0.79. In the mixed embodiment vs no embodiment conditions the overall perception of skill meters and explanation was greater with the mixed condition to a significant degree (U=67; p=0.007). This can be seen at an individual level with the following questions being higher for the robot condition by a significant amount: "I noticed that the system understood my skill levels" (U= 58; p= 0.002269), "I noticed that the system showed my skill levels" (U= 79; p= 0.023766). "I understood the explanation of why my skill levels were changing" were higher but not significantly so. When comparing the full embodiment and no embodiment conditions there was no overall significant difference, however the following question had a significant higher result: "I noticed that the system understood my skill levels" (U=84; p =0.037590). Other values again were higher but not significantly. Between the mixed embodiment and full embodiment there were no significant differences.

4.5 Trust in the model

The Cronbach's Alpha for the grouping of trust questions was 0.615, which is a rather low value. Overall there was no significant differences between any of the conditions. A more detailed review reveals no significant differences with respect to questions concerning the building of the model: "I trust that the system can gauge my skill levels correctly" and "I trust that the skill levels shown by the system were accurate". However, there were some significant differences with the following question: "I trust the explanation of why my skill levels are changing". In the mixed embodiment vs no embodiment conditions the value is higher in the mixed condition (U=80.5;p=0.044523). The fully embodied condition is higher than the no embodiment condition but not to a significant degree for the same question. The mixed condition leads to higher values than the fully embodied condition (U=80.5; p=0.026122).

5 Discussion

From these results it appears that embodiment has the largest effect in the explanation of the model. There is greater enjoyment with some amount of embodiment. There is greater perception that the system understands the learner. There is more trust in the explanation. The embodiment has less of an effect in respect to the perception of skill meters. This may be because the skill level is quite a simple concept to understand. The perception of skill levels changing and understanding that skills were changing was the same across all conditions. This was to be expected as this was made obvious in the experimental design. There was general consensus that the type of feedback provided, the skill meter and explanation were liked and understood across all conditions, which was encouraging for continued use of this feedback.

6 Conclusions

The results show promise for the introduction of a physical embodiment when providing feedback concerning skill levels, however to gain the most advantage the robot should be used to explain and elaborate rather than simply state skill levels. That there is trust in the explanation is very encouraging as this means that the learner may pay attention and act based on the explanation. Further analysis will investigate whether there were increased learning gains or greater evidence of reflection based on the task log data.

One limitation of this study is the absence of a comparison to a virtual embodiment. Such a comparison will enable analysis to explore if and to what extent the physical presence was responsible for the above results as opposed to other factors, such as the feedback being in a different medium. A further limitation concerned the skill meters. As they were not on the screen at all times this may have limited their use. However, limiting skill meters to a pop up allowed a closer comparison to robotic speech which can not be present all of the time.

This work is the starting point for further research in to open learner modelling in the field of educational social robotics. In the future the activity would be more complex to enable the learner to develop and exhibit skills in more depth. With a more complicated task that requires more planning there would be more opportunity for the student to reflect and exhibit other meta-cognitive strategies which if measured could allow more chance to detect if the student is utilising the skill based feedback. The robot should be able to interact with the student to a greater degree, this need not be very complex or cause distraction from the task; Head nods, facial expressions, and body position can provide unobtrusive feedback on the learner's utterances and actions without unnecessarily disrupting the learner's train of thought [9]. The behaviours can increase the immediacy [20] of the robot to engage and motivate the learner.

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